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Climate change impacts on rice productivity in the Mekong River Delta

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A R T I C L E I N F O

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A B S T R A C T

Rice is consumed by more people than any other grain. Globally, Vietnam is one of the largest exporters of rice, with the majority of production occurring in the tropical, low-lying Mekong River Delta. Agriculture in the Mekong River Delta is susceptible to yield losses from rising temperatures, sea level rise, and land use change as urban expansion replaces productive farmland. Most studies that assess climate change impacts to rice paddy yields are conducted at global- or continental-scales, and use general information on management practices to simulate production. Here, we use management information from farmers and published information on soils collected in Can Tho, a centrally-located province in the Mekong Delta. These data, along with projected mid-century (2040–2069) climate data for the RCP4.5 and RCP8.5 greenhouse gas emissions scenarios, are used to drive the Decision Support System for Agrotechnology Transfer (DSSAT) platform to project future rice paddy yields using the CERES-Rice model. The results indicate that yields decline for all three rice-growing seasons in Can Tho city for both emissions scenarios when CO_2 fertilization is not considered (5.5–8.5% annually on average depending on the emissions scenario). Increasing irrigation and fertilizer did not offset these losses, but simulated CO_2 fertilization did compensate for yield declines caused by increasing temperatures (yields were modeled to be up 23% higher when CO_2 fertilization is considered). However, we caution that estimated yield gains from CO_2 fertilization are optimistic, and these modeled values do not consider rises in ozone, which can diminish yields. Continued and future dam construction could negatively affect agriculture in the region, and current government policies prohibit rice paddy farmers from diversifying their livelihoods to adapt to these changes. Monitoring rice agroecosystems at a fine-scale, as this study does, is necessary to best capture the impact that varying management practices can have on local yields. When these differences are captured, future impacts of climate change can be modeled more effectively so that local policymakers can make informed decisions about how to offset yield losses and use farmland more efficiently.

1. Introduction

Earth's climate is rapidly changing, and alterations to global precipitation, temperature, and CO_2 regimes will likely have significant impacts on agricultural production. For example, the frequency and intensity of extreme heat is expected to rise (Luber & McGeehin, 2008), which could damage global food systems (Battisti & Naylor, 2009). While C_3 crops such as rice, wheat and soybean may benefit from increasing levels of CO_2, it is not yet clear whether the potential benefits will outweigh the detrimental impacts from rising temperatures (Long, Ainsworth, Leakey, & Morgan, 2005; Peng et al., 2004; Rosenzweig & Parry, 1994; Schmidhuber & Tubiello, 2007). Both droughts and floods are also anticipated to increase in frequency and intensity in the coming decades due to climate change, which could depress yields (Barnabás, Jäger, & Fehér, 2008; Rosenzweig, Iglesius, Epstein, & Chivian, 2001). To plan for and adapt to a changing climate, we need to explore how potential climate scenarios could impact different food-producing regions.

By 2050, a 100–110% increase in crop production is needed to sustain the global population (Tilman, Balzer, Hill, & Befort, 2011). An additional 2.7–4.9 million hectares (ha) of land per year would need to be converted to cropland to meet increasing production demands in the

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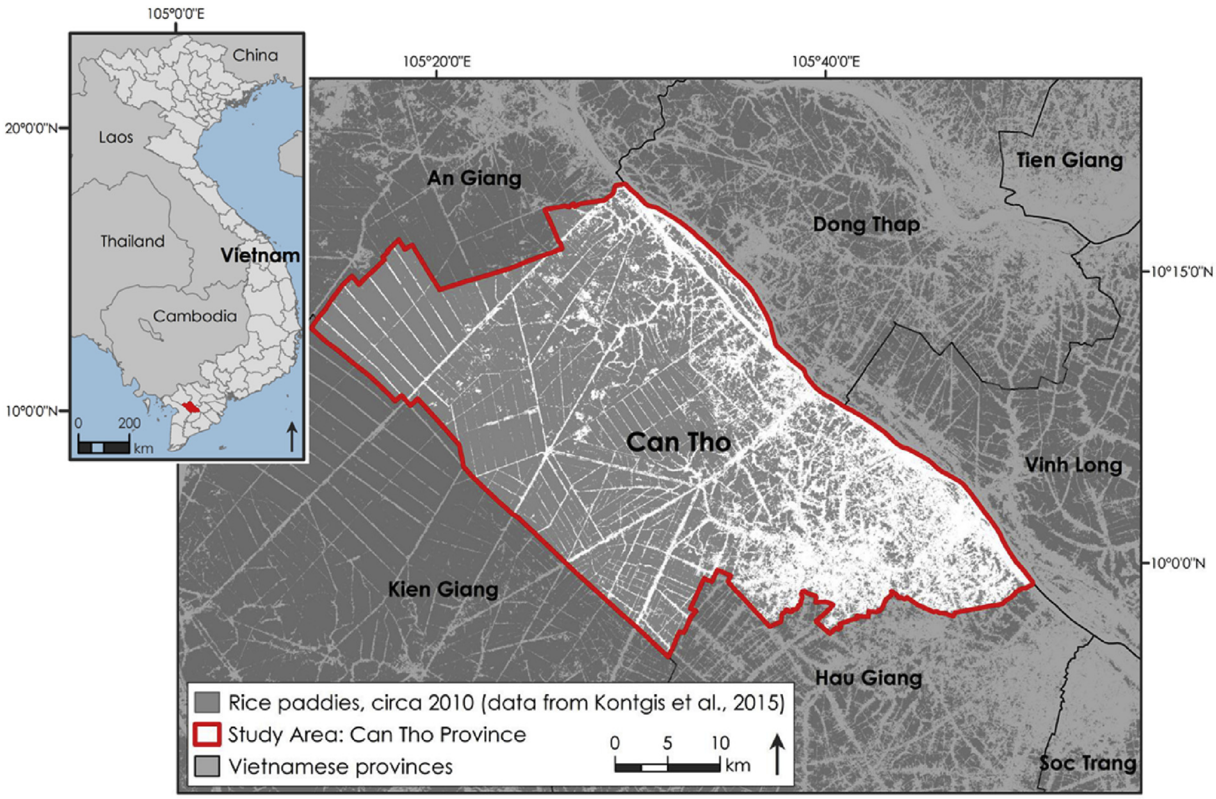

Fig. 1. The study area, Can Tho province. The area under rice cultivation (circa 2010) is shown for Can Tho and its neighboring provinces (Kontgis, Schneider, & Ozdogan, 2015).

future (Lambin & Meyfroidt, 2011). Agricultural expansion is often detrimental to fragile ecosystems, given that much of the potentially suitable agricultural land that is not already under cultivation lies in tropical rainforests (Ramankutty, Foley, Norman, & McSweeney, 2002). For food production to meet demand, yields must increase wherever possible, but not at the expense of other ecosystems. This could be achieved through continued plant breeding and by implementing better management practices that enhance production while minimizing cropland expansion (Tilman, Cassman, Matson, Naylor, & Polasky, 2002).

While climate change will affect agricultural production globally, rice (*Oryza sativa*) production is particularly important to model because rice feeds more people than any other staple food item (Maclean, Dawe, Hardy, & Hettel, 2002). Past studies have produced mixed results on how rice will respond to future climate change. While increasing nighttime temperatures have been associated with declining rice yields (Peng et al., 2004), some model results have suggested that CO_2 fertilization, which is the process by which rising atmospheric CO_2 levels can increase plant productivity (for a full discussion, see Kimball, 1983), will offset yield losses from rising temperatures (Bachelet & Gay, 1993; Erda et al., 2005; Gerardeaux, Giner, Ramanantsoanirina, & Dusserre, 2011). Other data have shown that any declines in future rice yields will be more dramatic at low latitudes compared to mid- and high-latitudes, because low-latitude production regions have warmer baseline temperatures, leading to greater heat stress for rice under future warming (Rosenzweig & Parry, 1994). Previous studies on the impacts of climate change on rice production and yields have been conducted on regional (Mall & Aggarwal, 2002; Matthews, Kropff, & Horie, 1997; Wassmann et al., 2009; Zhang & Tao, 2013) or global scales (Chen, McCarl, & Chang, 2011), or have focused on areas that are not necessarily important to global rice markets (Basak, Ali, & Islam, 2010; Fukai, 1999; Gerardeaux et al., 2011; Mahmood, Meo, Legates, & Morrissey, 2003; Subash & Ram Mohan, 2012). This study focuses on climate change impacts on rice in the Mekong River Delta, which is one of the world's most important rice-producing regions.

Vietnam provides a particularly interesting case study for examining how rice may respond to climate change. As a result of economic reforms targeting the agricultural sector in the late 1980s, Vietnam has become one of the world's largest exporters of rice, growing 90% of exported rice in the Mekong River Delta (Thanh & Singh, 2006; Wassman et al., 2010). The low-lying geography of the region leaves it vulnerable to sea level rise, salinity intrusion, and storm surge (Wassmann, Hien, Hoanh, & Tuong, 2004). Rising temperatures could have widespread and detrimental ramifications for rice production, which is the predominant land cover in a region where 65% of the income share comes from farming activities (Pandey, Paris, & Bhandari, 2010). People around the globe depend on the rice grown in the Mekong River Delta to supplement their diets, and the livelihoods of those who live in the delta rely on rice paddy farming. Despite these facts, there has been little research to quantify how the region will respond to future climate scenarios even though it faces acute threats from climate change.

With these issues in mind, the work presented here uses field-scale data to support modeling that examines how climate change could impact yields in the Mekong River Delta. The overarching goal of this paper is to assess how climate change and increasing CO_2 levels could impact rice paddy production, and how management practices could affect future yields. Specifically, this research aims to answer two research questions:

(1) How much will future climate change increase or decrease yields under projected climate scenarios in Can Tho city?
(2) Can different management strategies, such as increased irrigation or fertilizer application, mitigate climate-related impacts?

To answer these questions, we use the Crop Environment Resources

Synthesis (CERES) rice model within the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2010; Jones et al., 2003) modeling platform. First, the model was parameterized and validated using field-collected data on farmer management practices in Can Tho city, historical weather data, and census-reported values of rice paddy yields. Next, mid-century climate scenarios were used to determine the impacts of changing temperature and CO_2 concentrations on rice paddy yields. Finally, irrigation and fertilizer practices were altered to examine the ability of farmers to increase future yields with field-level decision-making. By answering these questions, this work aims to provide a deeper understanding of how climate change may affect the future of rice paddies, and, in turn, the future of rice paddy farmers in the Mekong River Delta. Here, we tie a global phenomenon – climate change – to a specific location to provide insights on how local systems will change in coming decades, as well as potential ways to adapt to that change.

2. Study area

This research focuses specifically on Can Tho city in the Vietnamese Mekong River Delta (VMD) region in southern Vietnam (Fig. 1). The city was formed in 2004, when the former Can Tho province split into two provinces: the current Can Tho city and Hau Giang province. Can Tho is a landlocked city that is centrally located in the delta and bordered by five other provinces. The province is subdivided into five urban districts (Binh Thuy, Cai Rang, Ninh Khieu, O Mon, and Thot Not) and four rural districts (Co Do, Phong Dien, Thoi Lai, and Vinh Thanh). The Hau River, a distributary of the Mekong, runs along the northeastern border of Can Tho city, separating it from Vinh Long and Dong Thap provinces. In the VMD, the weather is driven by the East-Asian summer monsoon, resulting in a dry season from December to late April and a rainy season from May to November. During the rainy season, the nine distributaries of the Mekong flood the delta from the end of September until late October or early November. Annual rainfall in the VMD averages nearly 2000 mm, with warm temperatures year round (20 °C - 35 °C).

In Vietnam, the Mekong Delta is home to > 17 million people, representing 20% of Vietnam's population, and has a population density of 429 persons km^{-2} (General Statistics Office of Vietnam, 2011a). The majority of the delta's land area is devoted to agriculture, with rice paddy as the predominant crop (General Statistics Office of Vietnam, 2011b). As of 2012, 65% (or 93,062.4 ha) of Can Tho's total land area was rice paddy, and 98% of these fields were harvested two to three times per year (Kontgis et al., 2015). The VMD is one of the only places in the world that has the technology, labor force, and climate to produce three crops of rice annually, allowing Vietnam to export over 6.5 million tons of rice per year (USDA Foreign Agricultural Service, 2015). The three growing seasons are: (1) winter-spring (đông xuân), which is planted in mid-November and harvested in February; (2) summer-autumn (hè thu), which is planted in mid-March and harvested in late June/early July; (3) autumn-winter (mùa thu), which is planted in mid-July and harvested in October. For each season, planting and harvesting dates are approximate and can vary year-to-year based on weather or management decisions. Both the physical and human dimensions of the Mekong geography make it a unique case study to examine both the geopolitical and physical impacts of climate change. Because the region is so densely populated and intensively farmed, ongoing changes in the delta affect farmer livelihoods, rice profitability, and the sustainability of a globally-important agro-ecosystem.

3. Methods

3.1. Modeling rice

For these analyses, we used DSSAT to run the CERES-Rice model, which is capable of simulating the growth of both dry-sown and hand-transplanted rice crops, and also adjusts for 'transplanting shock' on crop growth duration (Amien, Redjekiningrum, Kartiwa, & Estiningtyas, 1999; Singh, Ritchie, & Godwin, 1993). In addition, the rice module is capable of calculating water uptake under flooded and non-flooded conditions, and is designed to account for the effects of nitrogen-deficiency on photosynthesis and crop development (Amien et al., 1999). The daily rate of photosynthesis is calculated using daily accumulated solar radiation, day length, the light extinction coefficient within a canopy, light transmittance through a leaf, and leaf area index (Saseendran et al., 1998). Leaf area index is generated within CERES-Rice (rather than input into the model) based on phenological development of the plant as determined by growing degree day (GDD) accumulation (Mahmood et al., 2003). CERES-Rice uses the radiation use efficiency (RUE) approach to calculate net biomass production, and the impacts of rising CO_2 levels on RUE are modeled using curvilinear multipliers (Allen et al., 1987; Kim, Ko, Kang, & Tenhunen, 2013; Peart, Jones, Curry, & Boote, 1989). Specifically, RUE is calculated as follows (Allen et al., 1987):

$$RUE = \frac{R_m \times CO_2}{CO_2 + K_m} + R_i \tag{1}$$

where R_m is the asymptotic response limit of (R-R_i) at high CO_2 concentrations, R is the yield value, CO_2 is the carbon dioxide concentration, R_i is the intercept on the y-axis, and K_m is the value of the substrate concentration (*e.g.* CO_2) when (R-R_i) = 0.5 R_m.

This model has been tested in other Southeast and East Asian study areas where it has been used to predict rice yields and model water use efficiency, nitrogen use efficiency, plant phenology, and evapotranspiration rates (Cheyglinted, Ranamukhaarachchi, & Singh, 2001; Kim et al., 2013; Mahmood et al., 2003; Zhang & Tao, 2013). Further, comparative modeling studies have found that CERES-Rice is capable of simulating rice development more accurately than other rice crop models when the mean temperature is above the optimum temperature for rice (28–32 °C) (Wikarmpapraharn & Kositsakulchai, 2010; Zhang & Tao, 2013). DSSAT and CERES-Rice require three main categories of input variables: (1) weather, (2) crop management, and (3) land surface. Each of these input variables is discussed in detail below.

3.1.1. Weather data

In this study, we relied on two widely-used climate datasets: the NASA Prediction of Worldwide Energy Resources (POWER) database (Stackhouse, 2006) and the Agricultural Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) (Ruane, Goldberg, & Chryssanthacopoulos, 2015, Ruane, Winter, McDermid, & Hudson, 2015). POWER data is available from 1983 to present day, while AgMERRA is available from 1980 to 2010. For model calibration, we needed weather data from recent years (2004–2013) to correlate our modeled rice yields with available census data on rice yields for the study area. Since only the POWER database provides weather data for years after 2010, it was used to calibrate the model. This database provides daily maximum temperature (T_{max}), minimum temperature (T_{min}), solar radiation, relative humidity, wind speed, and precipitation data at a 1° spatial resolution, and has been used previously for DSSAT studies (White, Hoogenboom, Stackhouse, & Hoell, 2008).

To generate future climate scenarios, 30 years of present day climate (1980–2010) at a daily temporal resolution were used as a baseline for projections. We used AgMERRA for this because its data extend back to 1980. The AgMERRA climate forcing dataset was designed for the Agricultural Modeling Intercomparison Project (AgMIP) and other agricultural impact assessments (Ruane, Goldberg et al., 2015, Ruane, Winter et al., 2015). These data provide daily T_{max}, T_{min}, solar radiation, relative humidity, wind speed, and precipitation data at a 1/4° spatial resolution. To approximate atmospheric forcing data for all locations between 1980 and 2010, AgMERRA data combines information from a retrospective analysis of daily resolution climate data with in situ and remote sensing observations of temperature, precipitation, and

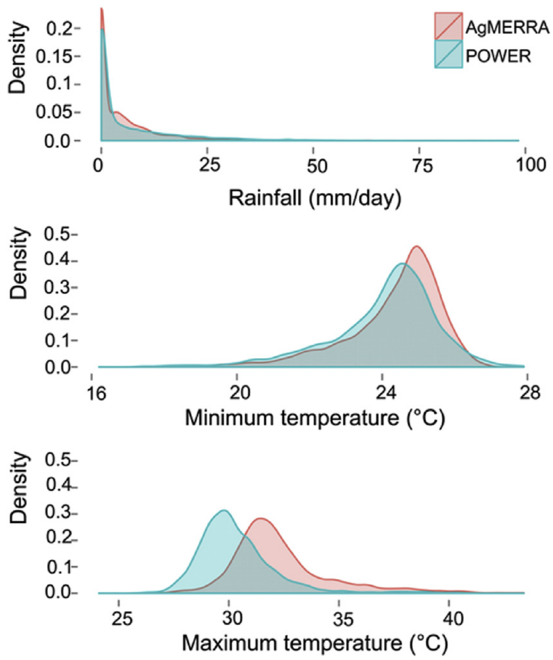

Fig. 2. This figure depicts density plots for rainfall, minimum temperature, and maximum temperature from the two weather datasets used in this analysis. The pink area depicts values from the Agricultural Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) climate forcing dataset developed for the Agricultural Modeling Intercomparison Project (AgMIP) (Ruane, Goldberg et al., 2015, Ruane, Winter et al., 2015), and blue areas depict values from the Prediction of Worldwide Energy Resources (POWER) database (Stackhouse, 2006). AgMERRA data was used in all model runs and to derive future climate change scenarios, while POWER data was used to calibrate the model. These density plots show that the distributions for each dataset are similar, such that the data can be used interchangeably. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

solar radiation (Ruane, Goldberg et al., 2015, Ruane, Winter et al., 2015). The AgMERRA distribution of values for T_{max}, T_{min}, and precipitation follows the same pattern as the POWER data, though AgMERRA has slightly higher temperature values (Fig. 2). Because AgMERRA was used to model yields under both present day and future climates, we do not expect this difference to significantly affect our results.

We modeled impacts to rice paddy for the mid-21st century (2040–2069) time period under two different emission scenarios drawn from the most recent Intergovernmental Panel on Climate Change (IPCC) assessment (AR5) (Collins et al., 2013). These scenarios are based on the total predicted radiative forcing by 2100 compared to pre-industrial levels, and are called representative concentration pathways (RCP). We analyzed future climate data under the medium-low emission scenario RCP4.5 (+4.5 W m^{-2} radiative forcing) and the high-emission scenario RCP8.5 (+8.5 W m^{-2} radiative forcing). To project mid-century climate data for these two scenarios, we employed AgMIP climate scenario generation tools (Ruane, Goldberg et al., 2015, Ruane, Winter et al., 2015), which generate future daily climate data for 20 different global circulation models (GCMs) (Table 1). All GCMs are driven with bias-corrected climate forcings, and the covariances between T_{max}, T_{min}, and precipitation are preserved from the baseline AgMERRA data (Hempel, Frieler, Warszawski, Schewe, & Piontek, 2013; Rosenzweig et al., 2014). Essentially, the AgMIP tool simply shifts the baseline (1981–2010) pattern of T_{max}, T_{min}, and precipitation to different degrees depending on the GCM and RCP scenario (Fig. 3).

3.1.2. Crop management data

For crop management, DSSAT requires the user to input (1) crop planting date, (2) planting method, (3) density at planting, (4) density at emergence, (5) soil nutrient fertilization (as opposed to fertilization that might occur from rising atmospheric CO_2 concentrations, as discussed in Kimball, 1983) rates and dates, and (6) irrigation amounts and dates. To gather these data for our study area, we met with farmers throughout Can Tho city to learn about their planting practices, and also gathered information from government offices in the city capital, Ninh Kieu district, during a field visit in March of 2015. Specifically, farmers shared information about their management practices, including fertilizer application and irrigation practices, what rice variety they planted, and rice phenology. For phenology, farmers provided approximate information for each growing season (winter-spring, summer-autumn, autumn-winter) on when rice was planted, when it emerged, when it reached its maximum height, and when it was harvested. During the calibration process, only planting dates were varied in order for yields to better match census values. All other management parameters (*e.g.,* variety, fertilizer timing/rates, irrigation timing/rates, planting method, density at planting/emergence) were held constant. Once calibrated (explained in section 3.2), the mean planting date for the 10-year calibration period (2004–2013) for each respective season was used for all model runs. All other management parameters were the same as in the calibration (Table 2).

3.1.3. Land surface data

The DSSAT model requires information on the soil type and properties of the study area. Soil information for Can Tho city came from published sources and information gathered during the March 2015 field visit (Khuong, Huan, Tan, & Hung, 2011; Watanabe et al., 2009) (Table 3). Can Tho is characterized by alluvial soils with a high concentration of organic matter due to the annual flooding of the Mekong River, which occurs during the rainy season (May–November) (Dobermann et al., 2002).

3.2. Model calibration

We calibrated the model using annual yields reported by the Vietnamese government (General Statistics Office of Vietnam, 2011b) in conjunction with the field-collected data on crop management, land surface, and weather. The census only provides yield information on winter-spring and summer-autumn rice paddy yields, and each of these growing seasons was calibrated independently. The model performed particularly well for the winter-spring season (Fig. 4A), but estimated higher yields than the census reported for the summer-autumn season (Fig. 4B). However, information from farmers and government officials led us to believe that yields for summer-autumn rice paddy were actually higher than what the census reports. Farmers estimated that summer-autumn yields were around 7000 kg/ha, while government officials suggested a value closer to 6000 kg/ha. Both farmers and officials also noted that recent winter-spring yields were the same as census-reported yields. No census information is provided for the autumn-winter growing season, so we compare relative trends of this season against the other two seasons based on information obtained during interviews. As suggested in the interviews, DSSAT estimates the lowest yields for autumn-winter and the highest yields for winter-spring (Fig. 5). The fact that modeled yields for each season follow the correct pattern over the ten-year time period further indicates that DSSAT is well-calibrated.

3.3. Model runs

To achieve our study objectives, three types of simulations were run using DSSAT. For all three experiments, land surface and crop management parameters were held constant, but present day weather was replaced with projected weather from the mid-century climate

Table 1
A list of the 20 global circulation models (GCM) used in this analysis to project mid-century climate scenarios.

Model number	Model name	Model source
1	ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation, Australia and Bureau of Meteorology, Australia
2	bcc-csm1-1	Beijing Climate Centre, China Meteorological Administration
3	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University, China
4	CanESM2	Canadian Centre for Climate Modeling and Analysis
5	CCSM4	National Centre for Atmospheric Research, USA
6	CESM1-BGC	National Science Foundation, Department of Energy, National Centre for Atmospheric Research, USA
7	CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organisation in collaboration with the Queensland Climate Change Centre of Excellence, Australia
8	GFDL-ESM2G	National Oceanic and Atmospheric Association Geophysical Fluid Dynamics Laboratory, USA
9	GFDL-ESM2M	National Oceanic and Atmospheric Association Geophysical Fluid Dynamics Laboratory, USA
10	HadGEM2-CC	Met Office Hadley Centre, UK
11	HadGEM2-ES	Met Office Hadley Centre with additional realizations contributed by Instituto Nacional de Pesquisas Espaciais, Brazil
12	inmcm4	Institute for Numerical Mathematics
13	IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France
14	IPSL-CM5A-MR	Institut Pierre-Simon Laplace, France
15	MIROC5	Atmosphere and Ocean Research Institute at the University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
16	MIROC-ESM	Atmosphere and Ocean Research Institute at the University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
17	MPI-ESM-LR	Max Planck Institute for Meteorology, Germany
18	MPI-ESM-MR	Max Planck Institute for Meteorology, Germany
19	MRI-CGCM3	Meteorological Research Institute, Japan
20	NorESM1-M	Norwegian Climate Centre

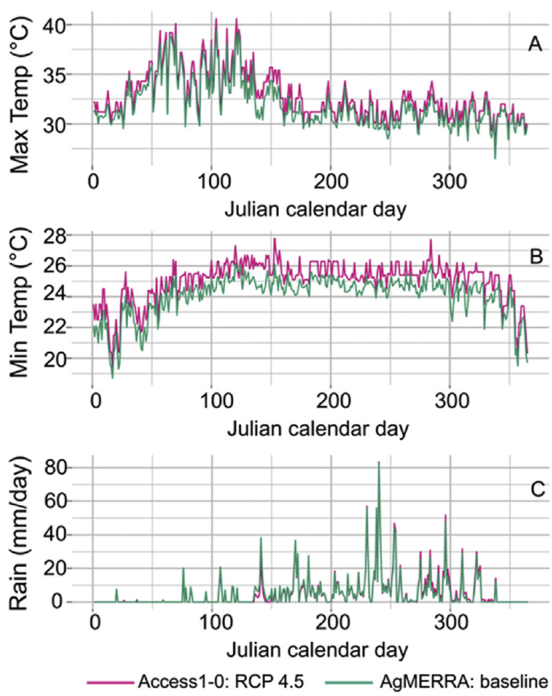

Fig. 3. All future scenarios from global circulation models (GCMs) were estimated with bias-corrected climate forcings, and the covariances between maximum temperature, minimum temperature, and precipitation were maintained from baseline data. This figure illustrates this by plotting a single GCM (ACCESS1-0) against the baseline AgMERRA data for RCP4.5. Projected maximum and minimum temperatures follow the same pattern as the baseline, but are slightly higher, while projected precipitation values nearly align with the baseline data. Note that all other GCMs were projected in a similar manner for each of the mid-century RCP4.5 and RCP8.5 scenarios.

projections. First, we simulated yields using climate projections from each GCM. These simulations held CO_2 values to baseline levels, and both RCP4.5 and 8.5 scenarios were run separately for each of the three planting seasons. Next, we ran the same simulations, but replaced the CO_2 values for each RCP scenario with future CO_2 concentration estimates from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor, Stougger, & Meehl, 2012). Lastly, we ran simulations to understand future potential yields by turning off the feature in DSSAT that models plant response to nitrogen and water stresses. Although these model runs represent a counterfactual scenario, they were performed to assess whether future yields could be improved by greater water or nitrogen availability. By default in DSSAT, plant response to water or nitrogen stress is modeled if the climate projections warrant it. To be clear, this does not mean that the plant is forced to experience stress, only that it will experience stress if available soil water or nitrogen is sufficiently low. For our final models, we re-ran the first two simulations (i.e., how yields respond to future climate scenarios with and without projected CO_2 concentrations) without simulating plant response to water or nitrogen stress. We were interested to see if anticipated yield declines associated with increased temperatures could be counteracted by different management practices. Specifically, we investigated the importance of irrigation and fertilizer applications to determine if increased water and nitrogen inputs could boost future yields.

3.4. Calculating production totals

While DSSAT estimates yields per ha in Can Tho, we were also interested in estimating total production across the entire municipality by mid-century. To do this, we used previously published results on the remote sensing-derived rice paddy area and number of annual harvests for 2012 (Kontgis et al., 2015). To calculate the total production values, we multiplied present-day and projected future yields by the total harvested area of Can Tho. Here, total harvested area is the total area of rice planted multiplied by the number of times it is harvested per year. In 2012, triple-cropped fields comprised over 62,000 ha of total land area (or > 66% of all rice) indicating that the total harvested area for triple-cropped fields was approximately 186,000 ha. Double-cropped fields were classified as > 29,000 ha (or, just under 32% of all rice), indicating that total harvested area was > 58,000 ha, and single-cropped fields had a total area (and total harvested area) of about 1400 ha (1.5% of all rice). Accordingly, the amount of total harvested area in Can Tho province is approximately 245,400 ha for all growing seasons. While the remote sensing-based maps show where single-, double-, and triple-cropped rice paddies are located, they do not reveal when these seasons are cultivated. For example, a double-cropped field might be cultivated during (A) winter-spring and autumn-winter

Table 2
The parameters used as input for management practices in DSSAT. These values were derived from interview field data gathered during March 2015.

Season	Planting date	Variety	Planting method	Density at planting (plants m^{-2})	Density at emergence (plants m^{-2})	Fertilization				Irrigation	
						Dates (no. days after planting)	Rates (kg ha^{-1})			Dates (no. days after planting)	Amounts (mm)
							N	P	K		
Winter-spring	November 18	IR64	Broadcast	250	150	10	20	24	10	5	30
						25	40	16	10	25	35
						45	40	–	20	35	40
										45	45
Summer-autumn	March 19	IR64	Broadcast	250	150	10	16	30	12	5	30
						25	32	20	12	25	35
						45	32	–	25	35	40
										45	45
Autumn-winter	July 20	IR64	Broadcast	250	150	10	16	30	12	5	30
						25	32	20	12	25	35
						45	32	–	25	35	40
										45	45

seasons, (B) winter-spring and summer-autumn seasons, or (C) summer-autumn and autumn-winter seasons. Since we cannot know for certain, we average yields across the growing seasons to calculate total production.

4. Results

4.1. Future climate scenarios

Compared to baseline climate data, mid-century T_{max} and T_{min} increased during all seasons for both RCP scenarios, and rainfall increased slightly for all seasons except summer-autumn (Fig. 6). To assess these general trends, projected temperature and precipitation values were averaged over all 20 GCMs for each RCP scenario. As expected, temperature increases were greater for RCP8.5 compared to RCP4.5 for all seasons, and T_{min} increased more dramatically than T_{max}. For example, average T_{max} increased 0.7–0.76 °C while average T_{min} increased 0.82 and 0.91 °C from baseline across all seasons for RCP4.5. For RCP8.5, average T_{max} increased 1.21–1.27 °C across all seasons, but average T_{min} increased 1.33–1.43 °C. For both RCP scenarios, the summer-autumn season is projected to experience the greatest changes to T_{min}, and is also projected to experience the greatest change to T_{max} for RCP8.5 (winter-spring season is estimated to have the greatest change to T_{max} for RCP4.5). Changes to average precipitation are negligible for all seasons, though in both RCP scenarios, small increases are projected for the winter-spring (0.09 mm day^{-1} for RCP4.5 and 0.084 mm day^{-1} for RCP8.5) and autumn-winter seasons (0.086 mm day^{-1} for RCP4.5 and 0.29 mm day^{-1} for RCP8.5). In contrast, small decreases are projected for the summer-autumn season in both RCP scenarios (−0.003 mm day^{-1} for RCP4.5 and −0.011 mm day^{-1} for RCP8.5).

4.2. CO_2 fertilization effects

For all 20 GCMs, the model runs that used mid-century climate data (2040–2069) and baseline CO_2 values (i.e. no CO_2 fertilization) produced lower yields compared to model runs using present day climate (1981–2010) (Fig. 7). For both RCP4.5 and RCP8.5, the summer-autumn season experienced the greatest variability in projections, with total yield estimates ranging from around 4000 to 7500 kg/ha.

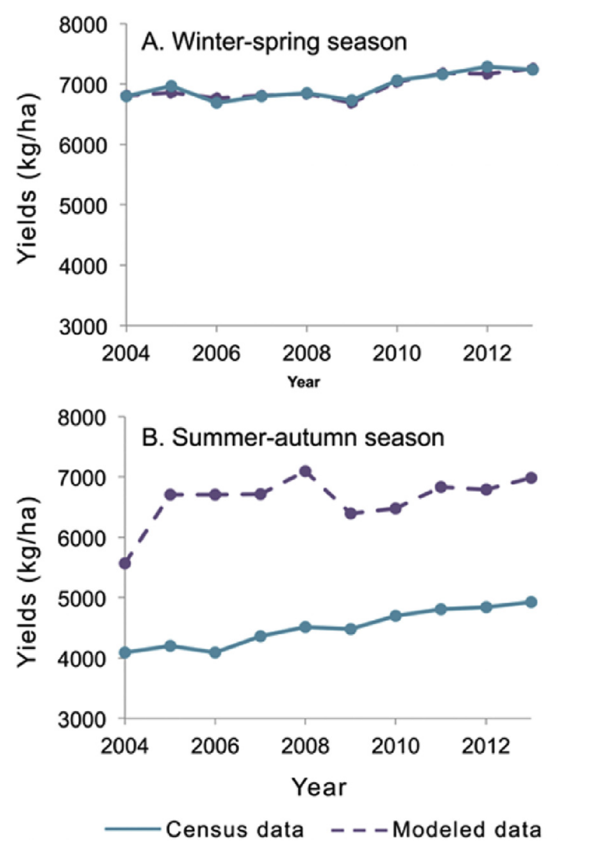

Fig. 4. DSSAT was calibrated using the Prediction of Worldwide Energy Resources (POWER) weather database (Stackhouse, 2006) and Vietnamese agricultural census data (General Statistics Office of Vietnam, 2011a,b,c). Can Tho province formed in 2004 when adjacent provinces split, hence calibration begins at this time point.

When estimated future CO_2 values were incorporated into the model runs, modeled yields increased across all seasons for all GCMs (Fig. 7). Unlike the model runs with baseline CO_2 values, models that

Table 3
The soil properties used in DSSAT for all model runs. These data were chosen based on published studies on soil properties for the study area (Khuong et al., 2011; Watanabe et al., 2009).

Clay (%)	Silt (%)	Stones (%)	Organic carbon (%)	pH	Cation exchange capacity (cmol/kg)	Total nitrogen (%)
45.4	54.5	0	1.34	5.0	4.5	0.15

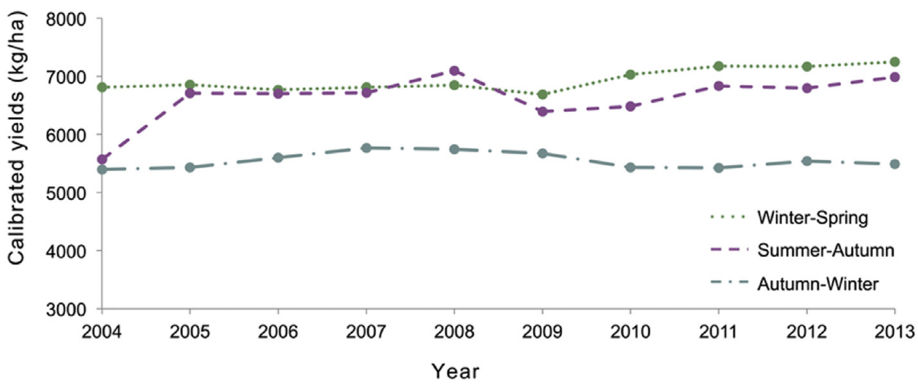

Fig. 5. DSSAT was calibrated against census data for the winter-spring and summer-autumn growing seasons, 2004–2013. The Vietnamese government does not provide census data on yields for the autumn-winter season in Can Tho province, but during interviews farmers stated that it was the lowest yielding season. While the absolute values of yields did not always correspond to census values, DSSAT captured seasonal patterns well.

incorporate CO_2 fertilization effects estimate that yields are highest for the summer-autumn season, followed by the winter-spring season. With CO_2 fertilization, summer-autumn again has the greatest amount of variability in yield estimates. For example, some estimated yields for RCP4.5 summer-autumn rice paddy are over 1000 kg/ha higher than the median baseline value, yet some outliers drop as low as 3000 kg/ha below the median baseline yield. Yield increases related to CO_2 fertilization effects are greater for all GCMs in RCP8.5, with potential yields exceeding 8000 kg/ha for the summer-autumn season.

Since there is often variability between the GCMs for a single season and RCP scenario, it is useful to combine the projected yield estimates from all 20 models to look at the differences between future and baseline yields (Fig. 8). When all yields are averaged over all 20 GCMs, several clear trends emerge. Without the simulated effects of CO_2 fertilization, yields across all seasons decline between present day climate and RCP4.5 (~200–300 kg ha^{-1}), and decline again between RCP4.5 and RCP8.5 (~200–300 kg ha^{-1}) (Fig. 8, left side). When simulated CO_2 values are incorporated, the opposite trend occurs, with yields increasing across all seasons from baseline to RCP4.5 and from RCP4.5 to RCP8.5 (Fig. 8, right side). Notably, potential yield increases with CO_2 fertilization are not as great as the losses estimated without CO_2 fertilization. For example, with CO_2 fertilization, average winter-spring yields are only projected to increase by 100 kg ha^{-1} from baseline to mid-century RCP4.5. This is smaller than the estimated loss of 300 kg ha^{-1} when CO_2 fertilization is not simulated. In short, yield estimates that account for CO_2 fertilization are the most optimistic realizations of the model.

For future yield estimates, the summer-autumn season has the potential to change drastically since it is the most affected by CO_2 (Fig. 9). For RCP4.5, mid-century yield estimates are 13% higher on average when CO_2 fertilization is simulated compared to when it is not. This value is nearly double the winter-spring season average percentage difference (7%), and more than double the autumn-winter average percentage difference (6%). The magnitude of change is greater for RCP8.5, where summer-autumn yields are 23% higher on average when CO_2 fertilization is simulated compared to model runs when CO_2 values are held to baseline levels. For both the winter-spring season and the autumn-winter season, yields are approximately 13% greater when CO_2 fertilization effects are simulated compared to when they are not.

4.3. Effects on total production

Once the yield estimates are converted to production totals, the average production in Can Tho is 1.67 million tons per year at baseline, averaged across all three growing seasons. Clearly, production trends will mirror yield trends, since the former is only scaling the latter by the total harvested area of the province (246,845 ha). By mid-century, the average total production of the province will decline to 1.59 and 1.55

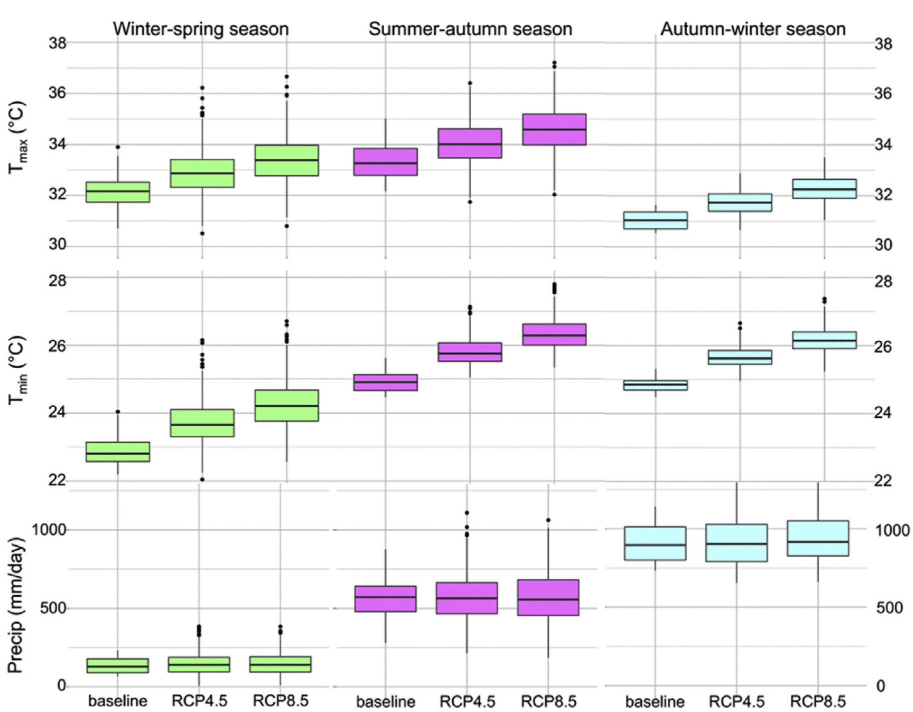

Fig. 6. For the RCP scenarios, all 20 global circulation models are included to get average differences between baseline and possible mid-century climate values. These results indicate that temperatures increase across all three seasons by roughly the same amount, and that modeled future precipitation is nearly equal to baseline values.

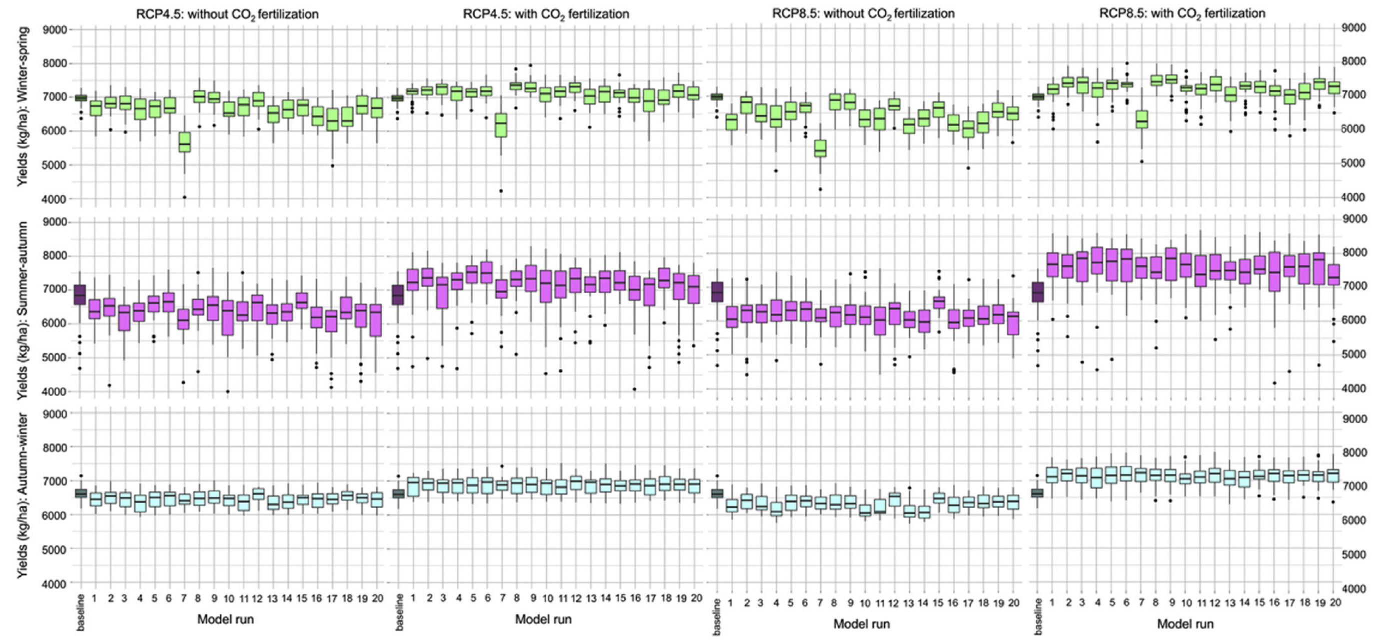

Fig. 7. The distributions of yield values for each of the 20 GCMs (along the x-axis) over the mid-century time period (2040–2069) with and without CO_2 fertilization illustrate that yields are higher when CO_2 fertilization is considered. The left two columns illustrate yields under the RCP4.5 scenario, while the right two columns illustrate yields under the RCP8.5 scenario.

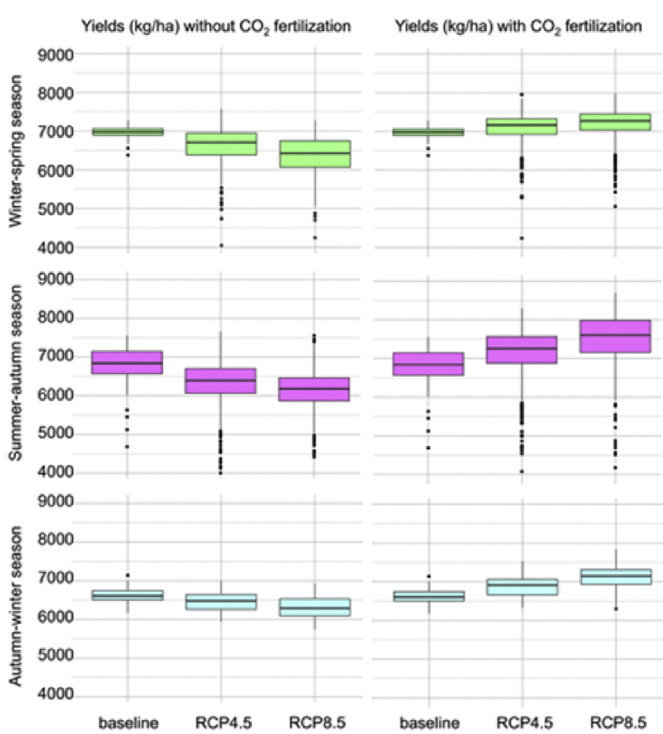

Fig. 8. Comparisons between baseline yield estimates and future ensemble yield estimates derived from all 20 global circulation models for both the RCP4.5 and RCP8.5 scenarios.

million tons under RCP4.5 and RCP8.5 emissions scenarios, respectively, when CO_2 fertilization is not considered. However, when CO_2 fertilization effects are simulated, the average total production increases to 1.74 million tons and 1.79 million tons by mid-century under RCP4.5 and RCP8.5, respectively.

4.4. Drivers of yield impacts

Upon discovering that yields are projected to decline without the potential benefit of CO_2 fertilization, we conducted a number of tests to investigate what is driving yield changes. Temperature was the strongest predictor of yields, which supports findings from other studies of rice paddies (Peng et al., 2004). In linear regression models that controlled for year-to-year differences in total seasonal solar radiation, increasing T_{min} and T_{max} were both correlated with lower yields regardless of whether baseline or projected CO_2 values were used in the model (Fig. 10). In other words, rising temperatures had negative impacts on yields even if concurrent rises in CO_2 have positive effects on yields. For rising T_{max}, this negative relationship is true for all seasons, but rising T_{min} is only associated with yield declines for winter-spring and autumn-winter. To better understand this discrepancy, we looked at correlations between T_{max} and T_{min} for all seasons (Fig. 11). These variables are highly correlated for winter-spring and autumn-winter (R^2 of 0.6 and 0.5, respectively), but not very well correlated for summer-autumn (R^2 of 0.2). The onset of monsoon season occurs during the summer-autumn growing season, so weather during this period can be volatile, which may explain the lower correlation between T_{max} and T_{min} during the summer-autumn season. T_{max} values are highest during the summer-autumn season, but T_{min} values are some of the lowest seen during the year. Because of this, stressful temperatures are far more likely to occur during the day than at night during the summer-autumn season, so yield declines are much more correlated with hot daytime temperatures than relatively cool nighttime temperatures.

4.5. Irrigation and fertilizer impacts on yields

All model runs discussed up to this point relate to climate change effects on future yields. The final model simulations address how management strategies could offset yield losses caused by rising temperatures. When water and nitrogen are not limiting factors for rice growth (*e.g.*, the water stress and nitrogen stress simulators in DSSAT were turned off), the variability in yield estimates increased across all seasons and both RCP scenarios (Fig. 12). Again, when CO_2 fertilization was simulated, estimated yields from the GCMs were generally higher

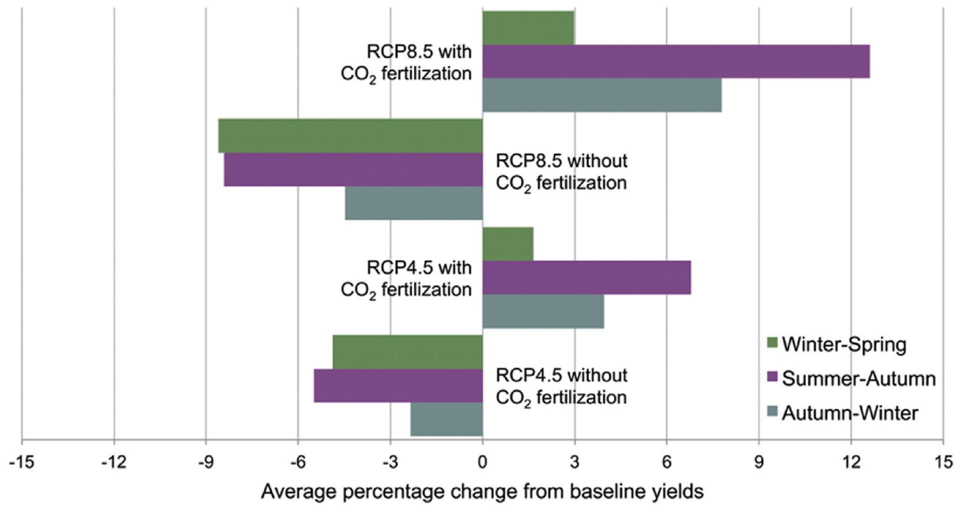

Fig. 9. The average percentage changes from baseline for all three seasons. For both RCP scenarios, average mid-century yields are lower than baseline when CO_2 fertilization is not simulated, while average mid-century yields are higher than baseline when CO_2 fertilization is simulated. The average percent changes from baseline are more dramatic for RCP8.5 compared to RCP4.5 for all seasons, while the summer-autumn season experiences the greatest changes from baseline. For reference, average baseline yields for winter-spring season are 6958.5 kg/ha, average baseline yields for summer-autumn season are 6668.2 kg/ha, and average baseline yields for autumn-winter season are 6611.0 kg/ha.

than both baseline yields and estimated yields when CO_2 fertilization was not simulated. However, the key point from this analysis is that for both RCP scenarios, eliminating water and nitrogen stress did not compensate for the negative impacts of rising temperatures on yields. Only the potential effects of CO_2 had the ability to offset future temperature-related yield declines in the model.

5. Discussion

As one of the most globally productive regions for rice, the Vietnamese Mekong River Delta is particularly important for rice markets, trade, and maintaining food stocks for the nearly three billion people that consume this staple food item across the globe. However, the agricultural systems in this area also face exacting challenges as warming temperatures are expected to decrease crop yields, at the same time that rising global populations will require more food. Additionally, the livelihoods of those in the VMD are inextricably tied to rice farming, and any changes to rice systems will affect the farmers as well. This research uses data from farmers in Can Tho city, Vietnam, in conjunction with projected mid-century climate data to model how rice paddy responds to warming temperatures and rising CO_2, and whether changing management practices can boost yields. The results show that without CO_2 fertilization, rice paddy yields will decline by mid-century by up to 5.5% under the RCP4.5 scenario and up to 8.6% under the RCP8.5 scenario. In addition, the results suggest that increased irrigation and fertilizer application cannot offset the losses caused by rising temperatures.

Similar to other studies that compare crop response with and without CO_2 fertilization, this analysis indicates that yields increase dramatically when simulated future CO_2 values are incorporated into the model. While this offers some hope that climate change could be a net benefit to food systems, some research has cast doubt on how much confidence scientists should put on this modeled yield boost (Long, Ainsworth, Leakey, Nösberger, & Ort, 2006). In the past, modeled effects of CO_2 fertilization have been based on decades-old enclosure studies that can significantly overestimate how much rising CO_2 concentrations will boost yields. However, the suite of CERES models estimate the effects of CO_2 on crop function and yields by employing findings from the Free Air Carbon Enrichment (FACE) open-air studies, which provide a more realistic crop response to CO_2 (Backland, Janetos, & Schimel, 2008; Hoogenboom, J, & PW, 2012). Yet even the heavily managed FACE plots cannot simulate the interactive effects of CO_2 rising in conjunction with other atmospheric gases like ozone, the rise of which is expected to lower future crop yields (Long et al., 2006). While some of our model results indicate that yields could experience a net increase by mid-century due to rising CO_2 concentrations, there is significant uncertainty that this will actually occur. Rather than relying on the most optimistic projections, policy decisions related to food production in the region should consider the full range of model outcomes.

Currently, Can Tho averages a total production of 1.67 million tons of rice annually, which is nearly 25% of total Vietnamese rice exports (USDA Foreign Agricultural Service, 2015). Based on our models, rising temperatures will cause total production to fall by about 70,000–120,000 tons of rice per year. Again, the effects of rising CO_2 may compensate for these losses, but rising temperatures will still negatively impact rice yields.

One way to compensate for temperature-related losses is to transition fields that are currently double- or single-cropped to triple-cropped fields. Doing so would add an additional 32,000 ha to the total harvested area of Can Tho city, or ~218,000 tons of rice per year (assuming that no additional land is converted to rice). While this could offset losses associated with climate change, it would also be highly resource intensive and environmentally devastating if management practices remain unchanged (Foley et al., 2011; Tilman et al., 2002). Further, it is unclear whether fields that are currently double- or single-cropped could be viably triple-cropped in the future. For example, if the fields are flood-prone or have poor soil quality, increasing the number of annual harvests may not even be possible. In addition, future changes to resource allocation in the region may render more annual harvests close to impossible. Given these challenges, there should be a strong commitment to double-cropped rice paddies that focus on farming during the most productive seasons.

Of the three rice-growing seasons, the summer-autumn season has the greatest variability in nearly all model runs. Summer-autumn also experiences the highest average T_{min} and T_{max} at present and in potential future climate scenarios. These high temperatures could be exceeding the temperature threshold for rice, which would result in highly variable yields that are lower on average than those produced in winter-spring, which has the lowest T_{min} and T_{max} at baseline and in future scenarios. If CO_2 fertilization were to occur as modeled, the variability of yields for the summer-autumn season could be worth the risk since its yields stand to increase so much compared to baseline (Fig. 9). However, if CO_2 fertilization effects are less than projected, the summer-autumn season is a risky time for farmers due to the high degree of variability in future estimates and the potential for big yield losses due to rising temperatures. Without the effects of CO_2 fertilization, average summer-autumn yields are projected to become the lowest of the three seasons by mid-century for RCP4.5 and RCP8.5. Because of this, farmers might consider focusing their efforts on winter-spring and autumn-winter seasons, which are projected to elicit higher, more stable yields.

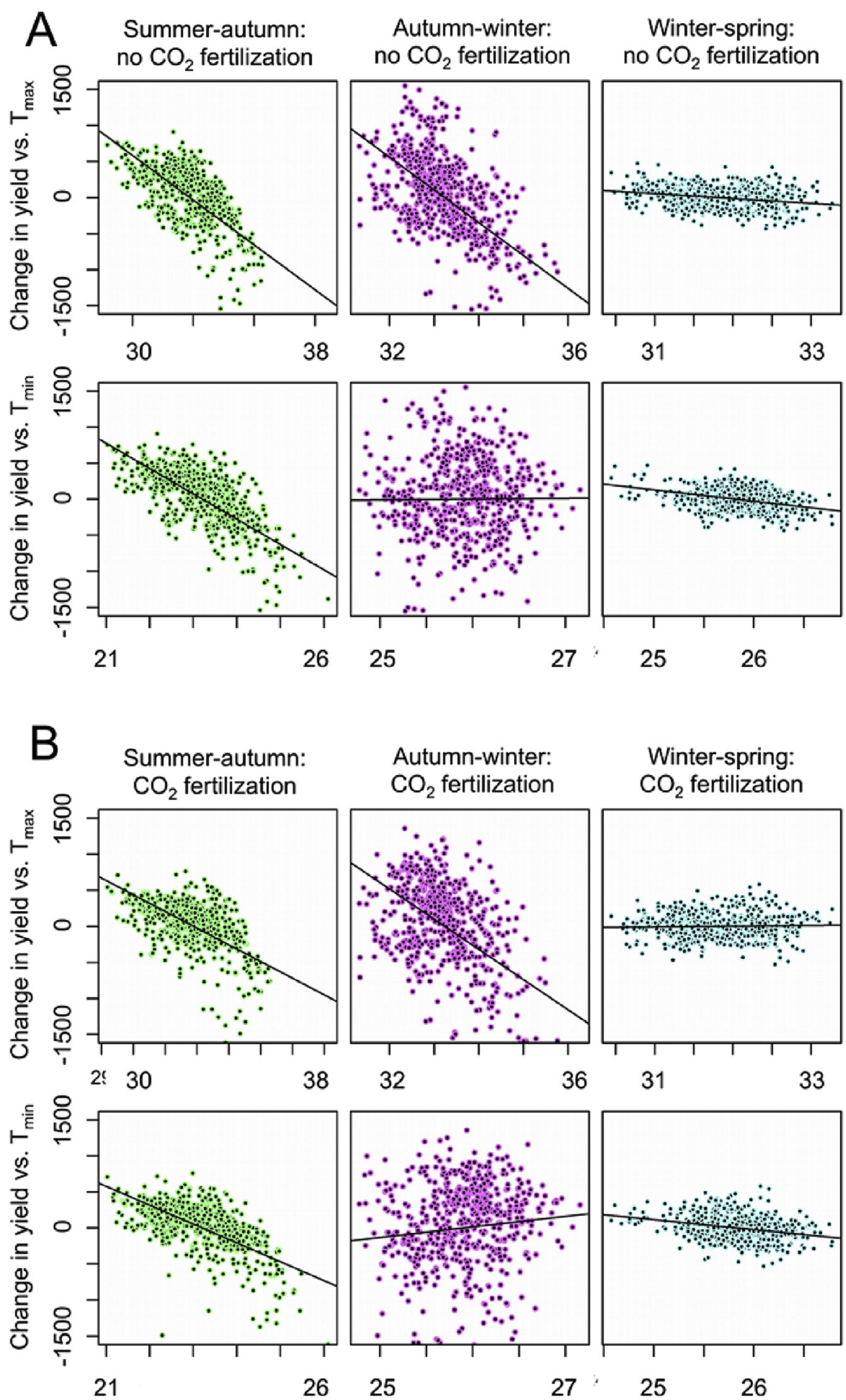

Fig. 10. Linear regression models of changes in yield vs. temperature changes that control for solar radiation indicate that both higher minimum and maximum temperatures are almost always correlated with lower yields for both (a) model runs that use baseline CO_2 concentrations and (b) model runs that use projected CO_2 concentrations. Summer-autumn minimum temperatures are a notable exception to this.

The control that the Vietnamese government exerts on all domestic agricultural activities predicates any potential changes to rice paddy yields that could be caused by climate change effects. Because rice is such an important crop in terms of employment, diet, and exports, the central government controls nearly all aspects of its production, and since 1992 this has meant setting annual target export values (Van Ha, Nguyen, Kompas, Che, & Trinh, 2015). Export goals are set by the government as a way to protect the poorest populations in Vietnam from higher rice prices, yet studies have shown that all income groups would benefit from free trade (Van Ha et al., 2015). Because of this policy, it is often more profitable for a rice farmer to let a field lie fallow than to farm it during a given season. Further, by requiring that rice exports meet a certain goal, farmers are given less freedom to diversify their agricultural practices, which could hinder their ability to adapt to a warming climate. As climate patterns shift, food production and rural livelihoods will benefit if farmers are given more freedom to decide what and when to plant.

Of course, broader geopolitics will also play a role in the food production of the region. Though it was beyond the scope of this study to investigate the impacts of dams along the Mekong, there is little doubt that new construction will greatly impact agricultural activities in the area (ICEM, 2010). The Laotian government has begun

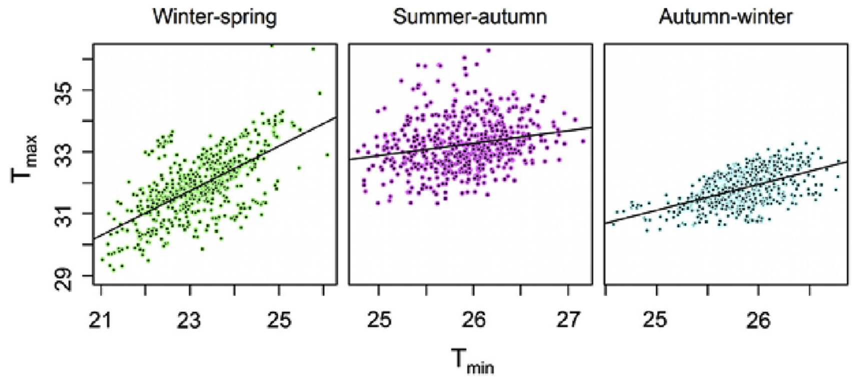

Fig. 11. Temperatures are correlated for both winter-spring and autumn-winter seasons, but the correlation is weaker for the summer-autumn season since the onset of the monsoon occurs during this season.

construction on the Xayaburi dam, which will be the first dam on the main stem of the Mekong outside of China. Ten other major dams are either being built or planned on the Cambodian and Laotian stretches of the river, which will add to China's seven functioning dams and five dams under construction on the upper part of the Mekong. While dams provide electricity generation and poverty alleviation, they also deplete fish stocks and flood villages (Grumbine & Xu, 2011; ICEM, 2010; Ziv, Baran, Nam, Rodriguez-Iturbe, & Levin, 2012). Water flow is expected to fluctuate greatly, particularly during the dry season when flows have already shown a declining trend (Lu & Siew, 2006). The dry season corresponds to winter-spring rice paddy, which is currently the highest yielding growing season with little variability projected under both RCP scenarios (Fig. 7). With less water and less sediment reaching the delta, rice yields will likely decline to a greater degree than this analysis shows (Chapman, Darby, Hong, Tompkins, & Van, 2016). Given these declines, many paddy farmers may switch to crops that require less water, which may further decrease total rice production.

Compounding potential production losses associated with decreased river flow, sea levels are projected to rise as the climate changes, which could completely inundate paddy fields with salt water (Smajgl et al., 2015). Though sluice and dyke construction in the Vietnamese Mekong Delta has flourished since markets opened in the late 1980s, there is evidence that these engineered landscapes increase flow velocity in the canals, leading to bank erosion and increased risk of flooding (Le, Nguyen, Wolanski, Tran, & Haruyama, 2007). Sea level rise is expected to not only flood coastal areas of thedelta, but also result in longer flooding periods in the central part of delta, near the study area for this paper (Van et al., 2012; Wassmann et al., 2004). Many farmers in the region cope with this change by also raising fish in their paddy fields, which results in a higher net income compared to farmers who solely plant rice (Berg, 2002; Phong et al., 2007). Livelihood diversification such as this is integral for the population of the delta to adapt to a changing landscape and climate. Rice production losses will need to be offset by expanding rice paddy into other regions or evolving technology that can keep paddies flourishing in southern Vietnam.

Rice paddies in the Mekong River Delta, and consequently the farmers who tend them, are facing potential future threats to production due to both climatic and geopolitical changes. Because of this,

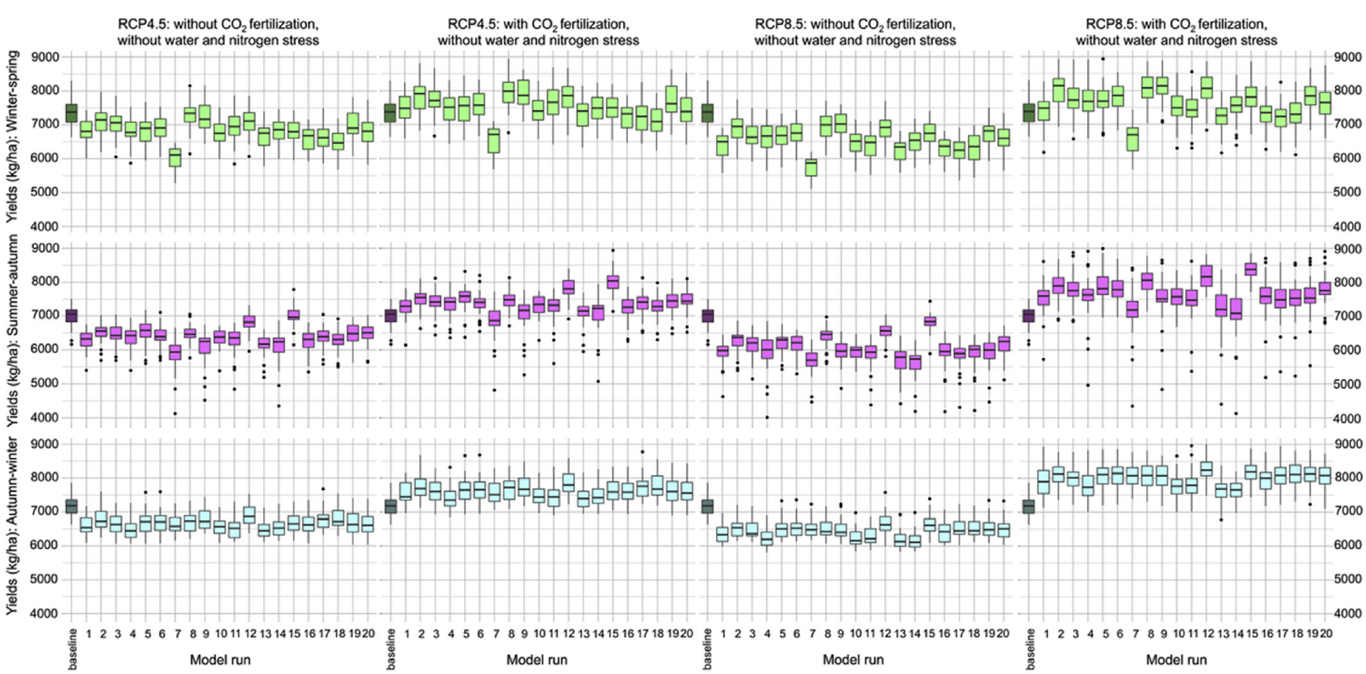

Fig. 12. To examine how management practices could compensate for yield losses in future scenarios (when CO_2 fertilization is not simulated), all DSSAT model runs were conducted again without water stress simulated. This was done to determine whether yield losses were due to water stress, which could possibly be rectified with increased irrigation, or to some other factor. Even without any simulated water stress on the rice plant, this figure shows that the distribution of yields are generally lower than baseline across all seasons and both RCP scenarios (4.5 and 8.5) without CO_2 fertilization, and higher than baseline with CO_2 fertilization.

farmers are confronted with a double exposure of dealing with not only the impacts of climate change but also the consequences of globalization (O'Brien and Leichenko, 2000). Neither biophysical factors nor the political ecology of the region alone can fully explain how rice production might change in the future. Both components must be considered together in order to understand the region's potential future. In this paper, we focused on the climatic piece of the puzzle, but we also point to other important socio-political factors that must be taken into account. It is likely that adaptations by seeds, farmers, and governments will all be necessary to ensure the productivity of rice in southern Vietnam and beyond.

6. Conclusion

Scientists, governments, and land-use planners face an immense challenge: we must find solutions to feed a rapidly growing global population while protecting our environment and the ecosystem goods and services it provides. This research illustrates the potential impacts on rice paddy yields due to climate change by mid-century in the Vietnamese Mekong Delta, with Can Tho as a case study for the region. Using field-collected data on land surface characteristics and management practices in conjunction with projected climate data for two different mid-century emission scenarios and 20 GCMs, we simulated rice production specifically for our study area. We found that yields decrease for all three growing seasons and all 20 GCMs for both future climate scenarios when CO_2 fertilization is not considered, but yields generally increase when CO_2 fertilization is taken into account. Notably, the temperature-related yield loss that is estimated for mid-century cannot be compensated for with greater inputs of water or nitrogen, indicating that altered management practices may not be able to offset losses. These losses will be compounded if sea level rise inundates coastal rice farms, or if upstream dams result in more variable or lowered river flow, and if farmers are not given more flexibility to adapt their agricultural practices. Because this region grows so much of the world's rice and the local community relies so strongly on rice farming, these agro-ecosystems need to be monitored so that paddy production and livelihoods are not lost due to future change.

Acknowledgments

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